Study and development of nature-inspired algorithm for intelligent manufacturing systems

A brief outline of the proposed research to be carried out in pursuance

for the award of the degree of

Doctor of Philosophy

in

Mechanical Engineering

Area of Research

Intelligent Manufacturing

Submitted by

R.S.S. Prasanth

Supervisor

Prof. K. Hans Raj

Faculty of Engineering

Dayalbagh Educational Institute

(Deemed University)

Dayalbagh, Agra 282005

(September 2012)

1.0 Introduction

Manufacturing plays a key role in any industrialized nation's economy. Currently, consumer driven global market is forcing manufacturing sector to become more agile so that it can meet the customized needs of the end users, economically in a short time. As high capital costs and machining costs add up to the cost of the product, there is a pressing need to operate machines as efficiently as possible with the optimal machine tool settings in order to achieve reasonable profits. Therefore, manufacturing processes essentially demand techniques that can determine optimal parameters and make a manufacturing system more cost effective. Traditionally, for any machining process to produce a machined product, a process planner selects the machining parameters from the available handbooks based on his experience. But, such selection of parameters does not yield optimal values and cannot minimize production cost, in dynamically changing production environment. Conventionally, researchers have been using deterministic optimization techniques such as geometric programming, dynamic programming, and branch-and bound techniques, which adopt specific rules to move from one solution to another and more often fail to give global optimum solution as they get trapped in local minima. Deterministic algorithms are difficult, computationally laborious and are not efficient when the practical search space is too large. Manufacturing processes are highly complex and non-linear with large number of continuous, discontinuous, mixed and non-explicit process variables and practical constraints, and therefore it becomes even more challenging to optimize them. But, selection of optimal process parameters for any manufacturing process is imperative as it significantly effects quality and cost of the work piece. So, there is a definite need of more easy to use, efficient, robust algorithms that can improve the effectiveness of machining, fabrication and, help in meeting the mutually conflicting objectives of current manufacturing environment, i.e., quality and cost. Nature Inspired Algorithms (NIAs), encompass the stochastic search techniques that draw inspiration from nature and are emerging as promising tools due to the fact that they can handle increasing complexity and uncertainty of real-world problems and can find acceptable results within a reasonable amount of time. Many practical uses of NIAs can now be found in various disciplines, including science and engineering [Odu05; Ray09; Jam11].

Therefore, it is proposed to study and develop NIAs for the optimization of intelligent manufacturing systems. The rest of the proposal is organized as follows. In section two, review of the literature is presented. In section three the proposed problem is discussed followed by the problem statement. In section four, objectives of the proposed research are presented. In section five the methodology of the proposed research is presented, which is followed by references.

2.0 Review of literature

The past two decades there has seen a rapid growth of interest in stochastic search algorithms, particularly those inspired by nature. Nature inspired algorithms emulate natural phenomenon from, biology, life sciences, physics etc. NIAs have been demonstrating impressive results on complex real world optimization problems. A common feature of NIAs is that the population of possible solutions to the problem is modified by applying some operators on the solutions based on their fitness, so that population is moved towards better solution of the search space.

2.1 Algorithms based on the principles of biology

Darwin's concepts of survival of the fittest have led to the development of several schools of Evolutionary Algorithms (EAs) such as, Genetic Algorithm (GA) [Hol75], Evolution Strategies (ES) [Rec84], Evolutionary Programming (EP) [Fog66] and Genetic Programming (GP) [Koj91]. Although GA, GP, ES and EP are popular evolutionary algorithms, GA is the most widely used one in the literature. Inspired by natural selection and molecular genetics, EAs define practical and robust optimization and search methodologies. As compared with conventional optimization methods, EAs provide a general approach to solving complex problems. Their global search capabilities, their flexibility, robust performance and adaptability are all considered as outstanding characteristics of EAs when searching for optimal solutions [Gex11].

GA is based on genetic science and natural selection and it attempts to simulate the phenomenon of natural evolution at genotype level while ES and EP simulate the phenomenon of natural evolution at phenotype level. The other popular evolutionary algorithm is Differential Evolution (DE) [Rai95] which has been particularly proposed for numerical optimization problems of continuous domain. In the basic GA, a selection operation is applied to the solutions evaluated by the evaluation unit. At this operation the chance of a solution being selected as a parent depends on the fitness value of that solution. One of the main differences between the GA and the DE algorithm is that, at the selection operation of the DE algorithm, all solutions have an equal chance of being selected as parents, i.e. the chance does not depend on their fitness values. In DE, each new solution produced competes with its parent and the better one wins the competition.

2.2 Algorithms based on the principles of life sciences

One important class of NIAs is the algorithms that emulate the behavior of living species. These cooperative algorithms are inspired by intelligent foraging behavior of social insects such as ants, birds, bees etc., and are named as swarm intelligence based

algorithms. Swarm intelligence is collective adaptation. A swarm intelligence based optimization algorithm emulates the behavior of organized, relatively less intelligent; population of biological species that collectively adapt to local rules and global environment and optimize the objectives. Bonabeau has defined the swarm intelligence as ‘‘. . . any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insect colonies and other animal societies. . .” [Bon99], a swarm can be considered as any collection of interacting agents or individuals. An ant colony can be thought of as a swarm whose individual agents are ants. An immune system can be considered as a swarm of cells and molecules.

2.2.1 Fundamental concepts of Swarm Intelligence (SI)

Two fundamental concepts, self-organization and division of labor, are necessary and sufficient properties to obtain swarm intelligent behavior such as distributed problem solving systems that self-organize and adapt to the given environment [Der05]:

Self-organization: Self-organization can be defined as a set of dynamical mechanisms, which result in structures at the global level of a system by means of interactions among its low-level components. These mechanisms establish basic rules for the interactions between the components of the system. The rules ensure that the interactions are executed on the basis of purely local information without any relation to the global pattern.

Bonabeau et al. have characterized four basic properties on which self organization relies: Positive feedback, negative feedback, fluctuations and multiple interactions:

- Positive feedback is a simple behavioral “rules of thumb” that promotes the creation of convenient structures. Recruitment and reinforcement such as trail laying and following in some ant species or dances in bees can be shown as the examples of positive feedback.
- Negative feedback counterbalances positive feedback and helps to stabilize the collective pattern. In order to avoid the saturation which might occur in terms of available foragers, food source exhaustion, crowding or competition at the food sources, a negative feedback mechanism is needed.
- Fluctuations such as random walks, errors, random task switching among swarm individuals are vital for creativity and innovation. Randomness is often crucial for emergent structures since it enables the discovery of new solutions.
- In general, self organization requires a minimal density of mutually tolerant individuals, enabling them to make use of the results from their own activities as well as others.

Division of labor: Inside a swarm, there are different tasks, which are performed simultaneously by specialized individuals. This kind of phenomenon is called division of labor. Simultaneous task performance by cooperating specialized individuals is believed to be more efficient than the sequential task performance by unspecialized individuals. Division of labor also enables the swarm to respond to changed conditions in the search space. Two fundamental concepts for the collective performance of a swarm presented above, self-organization and division of labor are necessary and sufficient properties to obtain swarm intelligent behavior such as distributed problem-solving systems that self-organize and -adapt to the given environment.

There are number of swarm intelligence based algorithms such as, Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Fireflies Algorithm (FA), Bee Colony Optimization (BCO), Bees Algorithm (BA), Artificial Bee Colony (ABC) algorithm, Cuckoo Algorithm (CA) etc. Among these algorithms, ACO, PSO and ABC have gained greater attention of the researchers, for numerical optimization.

Ant colony optimization (ACO) algorithm, which was introduced by Marco Dorigo [Dor96], is one of the successful strands of swarm intelligence that mimic the foraging behavior of social insects i.e., ants, particularly in the field of discrete optimization although ACO can also be applied to continuous optimization problems. Christian Blum et al., in his extensive survey [Chr05] found that ACO is applied on wide range of graph theoretic problems such as Travelling sales person, quadratic assignment, scheduling, vehicle routing, time tabling, bin packing, data mining, circuit and network design, bioinformatics etc.

Particle swarm optimization (PSO) algorithm is a popular swarm-intelligence-based algorithm, which was introduced by Eberhart and Kennedy in 1995 [Rus95]. PSO is also a population-based stochastic optimization technique and is well adapted to the optimization of nonlinear functions in multidimensional space. It models the social behavior of bird flocking or fish schooling. PSO has received significant interest from researchers studying in different research areas and has been successfully applied to several real-world problems.

PSO is employed on wide range of constrained science and engineering optimization problems such as ANN, face recognition, color image quantization, biomedical imaging (Infinite Impulse Response Filters), kinesiology, financial forecasting etc., [Ale08]. Number of swarm intelligence based algorithms that draw the inspiration from foraging behavior of bees have been reviewed in a recent technical report [Der09a]: Bee system in 1997, Bee colony optimization (BCO) in 2005, Honeybee search strategies in 2004, Virtual Bee Algorithm (VBA) in 2005, Bees algorithm (BA) in 2005, Bee swarm optimization (BSO) in 2005, Honey Bee Foraging (HBF) algorithm in

2007 etc. A variant of swarm intelligence based algorithm, that emulates the intelligent foraging behavior of a honeybee swarms named as artificial bee colony (ABC) algorithm was introduced by Dervis Karaboga in 2005 [Der05].

2.2.2 Motivation for ABC algorithm

In an exhaustive comparative study [Der09b] it is reported that ABC is better than DE, PSO, GA, and ES, on some standard unconstrained test functions of numerical optimization and with the advantage of employing fewer control parameters. In a study [Bah10], ABC algorithm was compared to that of the differential evolution (DE) and particle swarm optimization (PSO) algorithms on unconstrained large-scale well-known benchmark problems and found that the ABC algorithm has superior performance to the DE and PSO algorithms on large-scale unconstrained optimization problems since the ABC algorithm balances exploration and exploitation processes and employs different selection operators together: greedy selection, probabilistic selection and random selection. Further modified ABC algorithm has been proposed to solve engineering design problems. From their studies, it can also be noted that ABC algorithm is a promising tool for optimizing constrained engineering problems.

The ABC has been widely applied on numerical Optimization problems, Constrained optimization problems, Neural Network training, Medical Pattern Classification and Clustering, Traveling Sales Person problem, Leaf – Constrained Minimum Spanning Tree Problem, Network configuration, adaptive filtering, Economic Load Dispatch problem, grinding etc., [Der07; Der09b; Rao09b; Nad11; Nur11].

In a latest comprehensive review of ABC [Der12], it is reported that ABC algorithm is increasingly applied in different fields such as combinatorial optimization, neural networks, electrical power systems, chemical engineering applications, data mining, civil engineering applications, wireless sensor networks, image processing, electronics and control engineering applications, manufacturing optimization, etc. In a technical paper [Ivo11], an improved version of ABC for standard constrained engineering optimization problems is presented and showed relatively improved performance on certain test functions. Haiyan Zhao et al. [Hai10] developed a Hybridized ABC with GA by introducing two information exchange processes between GA population and bee colony to apply on four standard bench mark functions and reported that its performance is better than simple GA and quite comparable to ABC.

Milos Subotic, developed a multiple on lookers ABC for constrained optimization and tested on bench mark problems [Mil10]. Also from these results it can be seen that MO-ABC has more exploration power compared to the original ABC. In eight out of twenty four test functions, better results are obtained, with respect to ABC. Improved

ABC developed for standard engineering design optimization problems and compared its results PSO, but failed to obtain optimal values. Number of variants of ABC algorithm were reviewed and reported that like all other evolutionary optimization approaches, ABC also has some drawbacks. For example since it does not use an operator like crossover as employed in GA or DE. The distribution of good information between solutions is not at a required level. This causes the convergence performance of ABC for local minimum to be slow. These inherent limitations of ABC are required to be addressed [Der12].

2.2.3 The ABC algorithm

Artificial bee colony algorithm is essentially a population based stochastic search technique that mimics the intelligent foraging behavior of honey bees [Der05]. The ABC algorithm simulates the interactions of three artificial agents namely, employee bee, onlooker bee and scout bee. Each of these bees will perform a specific role in order to find the rich food source and to maximize the nectar amount unloaded at hive. The procedure of ABC algorithm [Der07] is presented below:

- Initialize (Send the scouts onto the initial food sources)
- Repeat
    - Send the employed bees onto the food sources and determine their nectar amounts
    - Calculate the probability value of the sources with which they are preferred by the onlooker bees
    - Send the onlooker bees onto the food sources and determine their nectar amounts
    - Stop the exploitation process of the food sources exhausted by the bees
    - Send the scouts into the search area for discovering new food sources, randomly
    - Memorize the best food source found so far
- Until requirements are met

2.3 Algorithms based on the principle of physics

The other important class of NIA is the algorithms that draw direct inspiration from the phenomenon of physics are Simulated Annealing (SA) [Kir83], Gravitational Search Algorithm (GSA) [Esm09] and Quantum Inspired Evolutionary Algorithm (QIEA) [Han00]. Simulated Annealing (SA) is a probabilistic method to find global minimum of a cost function that may possess several local minima. Simulated annealing essentially emulates the physical process whereby a solid is slowly cooled so that its structure is eventually frozen. Not all combinational optimization problems can be annealed to given satisfactory solutions and it converges very slowly. SA is often employed as a local search technique and appropriately hybridized with GA. Gravitational Search Algorithm (GSA) is more recent heuristic that exploits law of gravitation, and is introduced by Esmat Rashedi, Hossein Nezamabadi-pour, and Saeid

Saryazdi in 2009 [Esm09]. The performance of GSA is compared theoretically with PSO (Particle Swarm Optimization) and CFO (Central Force Optimization) a deterministic algorithm. It is reported that better results can be achieved by using additional local search technique into GSA.

The other popular evolutionary algorithm that draws inspiration from behavioral phenomenon of physical particles in nature is quantum-inspired evolutionary algorithms (QIEAs). QIEAs are one of the three main research areas related to the complex interaction between quantum computing and evolutionary algorithms, which are receiving renewed attention. A quantum-inspired evolutionary algorithm is a new class of NIAs suitable for a classical computer rather than for quantum mechanical hardware. Moore and Narayanan 1996 first attempted to exploit some of the principles of quantum mechanics, such as Q-bits, superposition, quantum gates and quantum measurement, in order to solve various problems using a classical computer [Nar96].

2.3.1 Quantum concepts

Like a quantum mechanical system, a quantum-inspired system may also be regarded as a probabilistic system, in which the probabilities related to each state are utilized to describe the behavior of the system. QIEAs use quantum notation, quantum-inspired bits (Q-bits), quantum superposition, quantum-inspired gates (Q-gates) and observation processes to specify their state and position. More specifically, Q-bits are applied to represent genotype individuals; Q-gates are employed to operate on Q-bits to generate offspring; and the genotypes and phenotypes are linked by a probabilistic observation processes.

Quantum notation: Bra-Ket: A standard and customary notation for describing quantum states in the theory of quantum mechanics composed of angle brackets and vertical bars. It is so called because the inner product (or dot product) of two states is denoted by a **brac**k**et**, <ø|ψ>, consisting of a left part, <ø|, called the **bra** (pronounced /'braː/), and a right part, ψ>, called the **ket** (pronounced /ket/). This notation is known as Dirac notation. The expression <ø|ψ>, is typically interpreted as the probability amplitude for the state ψ to collapse into the state ø

Superposition: Quantum superposition is a fundamental principle of quantum mechanics. It holds that a physical system exists in all possible states simultaneously; but, when measured, it gives a result corresponding to only one of the possible configurations. If, in a system there are, *m* Q-bits, it can represent 2^m states at the same time, but by measuring it collapses to a single state.

Q-bit and its observation: Classically representation of solutions can be classified as binary, numeric, and symbolic [Hin99]. In contrast, a QIEA uses the Q-bit representation, a novel probabilistic description of Q-bit individuals as strings of Q-bits.

The Q-bit is the basic computing unit in a QIEA, which may defined as pair of complex numbers that specify probability amplitudes of the corresponding state and represented as $[\alpha\ \beta]^T$ where the numbers α and β satisfy the normalization condition $|\alpha|^2 + |\beta|^2 = 1$. And, as in quantum theory, the values $|\alpha|^2$ and $|\beta|^2$ denote the probabilities that the Q-bit will be found in the '0' or '1' state, respectively. By a process of probabilistic observation, each Q-bit can be rendered into one binary bit. This very phenomenon of Q-bit make it quite suitable for evolutionary computation as it possess the both exploration and exploitation characteristics which are very crucial in evolution computation [Han02].

Quantum gate: In QIEA, the concept of updating a solution in the process of evolving the quantum bits is solely dependent on the quantum gate employed in the algorithm per se. There are number of quantum gates such as Rotation, Hadamard, Pauli, CNOT etc. In QIEAs mostly rotation gate is employed that updates the q-bits.

2.3.2 Motivation for Quantum Inspired Evolutionary Algorithms (QIEAs)

Quantum-inspired evolutionary algorithms, one of the three main research areas related to the complex interaction between quantum computing and evolutionary algorithms, are receiving renewed attention. Although QIEAs were firstly introduced by Narayanan and Moore in the 1996 [Nar96], to solve the traveling salesman problem, in which the crossover operation was performed, based on the concept of interference. Han and Kim better exploited the principles of quantum mechanics in their version of QIEA [Han00] and this captured the attention of researchers from varied disciplines. Quantum Inspired Evolutionary Algorithms are applied on numerous problems of various application domains [Gex11] such as Knapsack problem, Image segmentation, Function optimization, Disk allocation, Job Scheduling, Floor shop scheduling, Face versification, unit commitment, economic power dispatch, Bandwidth adaption, SVM parameter selection, Ceramic grinding, Engineering design optimization problem etc.

Although the advantages of these NIAs are multifold, including their simplicity, robustness and flexibility, but there is little reason to believe that one algorithm would find best solution to all optimization problems. This is in accordance with the No Free Lunch theorem, which explains that for any algorithm, any elevated performance over one class of problems is exactly paid for in performance over another class [Gro07]. Therefore these advantageous features of two different algorithms may be used to form a hybrid or augmented technique so as to improve the quality of the solution. Researchers have developed such hybrid algorithms to solve real world engineering optimization problems. Few examples of such hybridized algorithms are: Genetic Simulated Annealing Algorithm (GASAA) [Wan05], Hybrid Immune Algorithm that combines the benefit of Artificial Immune Algorithm and Hill Climbing local search algorithm [Yil09] and a quantum particle swarm optimizer with chaotic mutation operator [Lea07] etc.

K Hans Raj et al. [Han04] developed a Neuro-Fuzzy Hybrid Stochastic Search Technique (NFHSST) for multi-objective process optimization of hot closed die forging for intelligent manufacturing. K Hans Raj et al. [Han05] developed evolutionary computational technique (ECT) that integrates GA and SA and applied for constrained engineering design optimization problems. And this ECT is further extended by integrating quantum principles and developed Quantum Seeded Evolutionary Computation Technique (QSECT) for constrained engineering design optimization. They also developed Quantum Hybrid Stochastic Search Technique (QHSST) for solving constrained optimization problems. This algorithm is based on concepts and principles of quantum computing that take advantage of quantum parallelism and uses evolutionary algorithm as a basic programming technique. It is hybridized by incorporating various other soft computing techniques such as Artificial Neural Network (ANN), Quantum Neural Network (QNN) or Adaptive Neuro Fuzzy Inference System (ANFIS) for fitness estimation which results in rapid convergence to better solutions [Han07].

According to a latest comprehensive survey on QIEAs presented by Gexiang Zhang [Gex11], the research conducted so far depicts the QIEA as more versatile evolutionary algorithm with a lot of promising features and many potential applications. QIEAs have successfully been employed to solve some engineering optimizations such as digital filter design and image processing. However, the potential of QIEAs has hardly been explored for engineering applications, compared with other optimization methods such as particle swarm optimization.

2.3.3 Procedure of Quantum Inspired Evolutionary Algorithm (QIEA)

Quantum inspired evolutionary algorithm (QIEA) is essentially population based evolutionary algorithm for classical computer. The basic procedure of QIEA [Han00] is presented below:

begin
    $t \leftarrow 0$
    initialize $Q(t)$
    make $P(t)$ by observing $Q(t)$ states
    evaluate $P(t)$
    store the best solution among $P(t)$
    While (**not** termination – condition) **do**
    begin
        $t \leftarrow t + 1$
        make $P(t)$ by observing $Q(t\text{-}1)$ states
        evaluate $P(t)$
        update $Q(t)$ using quantum gates $U(t)$
        store the best solution among $P(t)$
    end
end

2.4 Literature review of manufacturing optimization

Modeling and optimization of machining processes has attracted many researchers as this significant impact on total production cost [Cha10]. Recently, James M. Whitacre [Jam11] in their paper presented strong evidence that the use of Nature Inspired Meta-heuristics (NIMs) is not only growing, but indeed appears to have surpassed Mathematical Optimization Techniques (MOT) and other meta-heuristics. Some notable industrial organizations that use of evolutionary algorithms are: General electric, Dow AgroSciences, PRECON S.A., A Chilean Foundry Company, Far East electromechanical manufacturing plant, and many of the automobile and aircraft industries.

2.4.1 Literature review of modeling techniques of manufacturing systems

Selection of process parameters is an imperative and challenging task in any manufacturing environment, as that can give us optimum performance of machines and lead us to quality products and good profits. The demanding problem of tradeoff between quality and cost is long standing challenge, for which researchers are applying number of procedures and techniques. For any manufacturing system optimization the essential pre requisite is to have a representative model which incorporates all the process variables and practical constraints of manufacturing environment. Therefore, researchers have been using different modeling procedures that have been useful to represent the complete behavior of manufacturing systems. A statistical regression technique popularly known as Response Surface Methodology (RSM) is a simple modeling technique that has several advantages compared to traditional methods in which one variable at time technique is varied [Box87]. RSM provides large amount of information from small number of experiments and facilitates to observe the complex interaction among dependent and independent variables with aid of empirical equation [Car00].

Researchers are leaning more on this multiple regression technique as it can give more representative empirical relation between input and output of any process with minimal data. Multiple regression analysis and neural networks are also equally effective. The major limitation to the use of neural networks and fuzzy sets is that it requires large set of experimental data [Cha10]. Therefore, the optimization of ANN, ANFIS, RSM models that fully represent the manufacturing processes is a very difficult activity. Complex mathematical optimization approaches often fail to give optimal results and struck in local optima [Deb01]. So, researchers are exploring more flexible and robust algorithms that can handle uncertainty [Odu05; Cha10], that are simple to implement than their counterparts, and can produce repeatable results in reasonable time.

2.4.2 Literature review of machining operations

Machining and joining are the two popular manufacturing processes, the other two being forming, and casting. The focus of this review is on the application of NIAs to modeling and optimization of machining processes such as turning, grinding, milling, drilling, and fabrication process namely friction stir welding.

2.4.2.1 Literature review of turning optimization:

T. Srikanth and V. Kamala [Sri08] experimentally determined optimal speeds for alloy steels and developed a mathematical model for minimum surface roughness for plane turning and applied a real coded genetic algorithm for the optimization such process. Ali Rıza Yıldız [Ali09] applied a novel particle swarm optimization approach i.e., a new hybrid optimization approach named Particle Swarm - Receptor Editing (PSRE) is presented for product design and manufacturing and compared its performance with a hybrid genetic algorithm, scatter search algorithm, genetic algorithm, and integration of simulated annealing and Hooke-Jeeves pattern search.

Zoran Jurkovic et al., [Zor10] applied different optimization methods to minimize the surface roughness in longitudinal turning and used classical experimental design method. They reported the advantages of multiple regression method over Taguchi method. Tangential turn-milling using DE [Pra11a], plane turning, using DE [Pra11b], using ABC [Pra11c] and using QIEA [Pra12] to achieve batter surface finish are attempted.

Pinkey Chauhan et al., [Pin11] developed a real coded genetic algorithm equipped with LXPM cross over operator and differential evolution algorithm and applied it on CNC turning optimization problem. The performances of both the algorithms are compared with several other optimization algorithms like PSO, Binary GA, SA, DE, NMS, and BSP. In a study [Cha12], the performance of polycrystalline diamond (PCD) cutting insert has been described using response surface methodology for turning of titanium (Grade-5) alloy. The machining parameters such as cutting speed, feed rate, depth of cut, and approach angle of the cutting edge of turning operation have been considered in the investigations. Empirical models of tangential force and surface roughness have been developed and optimized

2.4.2.2 Literature review of grinding optimization:

R V Rao and P J Pawar [Rao09b] applied artificial bee colony, harmony search, and simulated annealing algorithms for process optimization of grinding and studied their

performance in terms of convergence and quality of the solution. They considered production cost, production rate, and surface finish subjected to the constraints of thermal damage, wheel wear, and machine tool stiffness as objectives for optimization. Results are also compared with quadratic programming, genetic algorithm and differential evolution algorithm. They reported that ABC algorithm outperformed all other algorithms, i.e. quadratic programming, GA, HS, and SA, showing significant improvement over quadratic programming.

V. Janakiraman and R. Saravanan [Jan10] attempted to concurrently optimize the manufacturing cost of piston and cylinder components by optimizing the operating parameters of the machining processes. The concurrent optimization problem was to minimize total manufacturing cost and quality loss function. Genetic algorithm is used for optimizing the parameters, and they successfully reduced the manufacturing cost without violating any constraints.

Kuo-Ming Lee et al., [Kuo11] developed a hybrid differential evolution algorithm (DEA) embedded with Taguchi technique called Taguchi – sliding Based Differential Evolution Algorithm (TSBDEA) for the optimization of grinding operation.

2.4.2.3 Literature review of milling optimization:

Vedat Savas and Cetin Ozay [Ved08] enumerated average surface roughness model for tangential turn-milling and applied a genetic algorithm to estimates optimal cutting parameters, and compared GA predictions with his experimental results. H. Öktem [Okt09] developed surface roughness to model and optimize the cutting parameters when end milling of AISI 1040 steel material with TiAlN solid carbide tools under wet condition. He further applied genetic algorithm for its optimization.

Tongchao et al., [Ton10] developed two empirical models for cutting forces and surface roughness are established, and ANOVA indicates that a linear model best fits the variation of cutting forces while a quadratic model best describes the variation of surface roughness. Surface roughness under some cutting parameters is less than 0.25 μm, which shows that finish hard milling is an alternative to grinding process in die and mold industry.

Kantheti Venkata Murali Krishnam Raju et al., [Kan11] developed a surface roughness to model and optimize the cutting parameters of end milling for workpiece 6061 aluminum alloy with HSS and carbide tools under dry and wet conditions, and applied a genetic algorithm to minimize the surface roughness. In a study [Nat11], response surface methodology was used for the optimization of machining parameters of micro end milling and they developed statistical models for the MRR and Ra using

central composite design with three level factors. Researchers [Kov12] developed regression model and a fuzzy model for face milling operation to predict surface roughness in dry machining.

According to a technical report [Lak12], the average surface roughness values obtained when milling EN24 grade steel with a hardness of 260 BHN using solid coated carbide tools were modeled and optimized using response surface methodology. Input variables consist of cutting speed (v), feed rate (f) and depth of cut (d).The output variables are surface roughness and Material removal rates. It is found that the roughness tends to decrease with decreasing feed and increasing cutting speed.

2.4.2.4 Literature review of drilling optimization:

Erol Kilickap et al. [Ero11] developed an empirical model of surface roughness for drilling of AISI1045 and applied genetic algorithm for its optimization. By such optimization method, it is reported that noticeable saving of machining time and production cost can be achieved.

R. Venkata Rao and V.D. Kalyankar [Ven12] developed a new evolutionary algorithm called Teaching-Learning Based Optimization (TLBO) algorithm and applied on drilling, grinding and turning optimization and reported that the TLBO is better than GA, Adaptive QIEA.

Rajmohan and Palanikumar [Raj12] performed the multiple performance analysis in machining characteristics of drilling hybrid metal matrix composites produced through stir casting route. The developed an empirical model has been developed for predicting the surface roughness and burr height in drilling of Al 356/SiC-mica composites. The optimization results showed that the combination of medium spindle speed, low feed rate, and high wt% of SiC is necessary to minimize burr height and surface roughness in drilling hybrid composites.

2.4.2.5 Literature review of Friction Stir Welding (FSW):

The FSW process has advantages as it can weld materials that are difficult to weld using conventional processes. Friction stir welding has many metallurgical, environmental and energy benefits. Joining metallic structures produced by Equal Channel Angular Pressing (ECAP) using conventional joining processes may alter the ultra fine grain structures produced. Many of these problems are eliminated by FSW, a solid state welding process. A rotating tool plunges into a part where the material plastically deforms due to an elevated temperature field produced by adiabatic heating. The tool traverses along, or across, the intersection of two parts, joining the parts as the

tool leaves the processing zone and deformed material fills the void left by the tool, as shown in figure - 1.

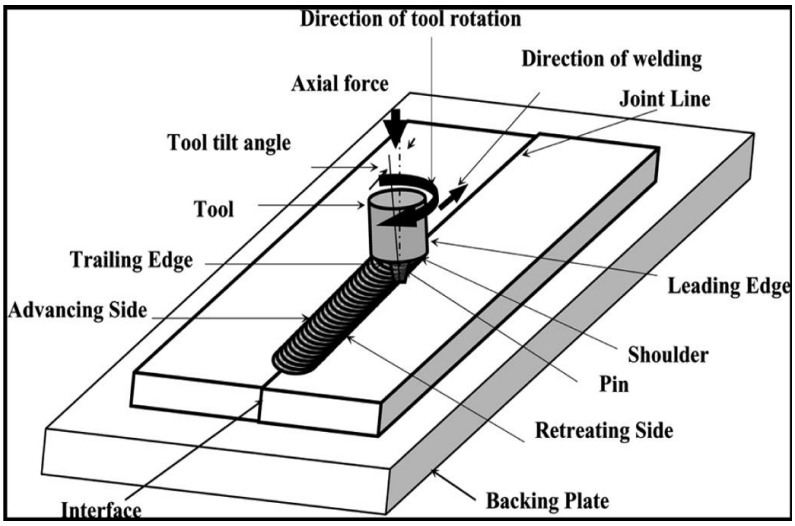

Figure - 1: A schematic diagram showing friction- stir welding process [Sur11]

But, FSW process parameters such as tool rotational speed (rpm), welding traverse speed (mm/min), plunge depth (mm), geometrical shape of the tool (conical, square etc.), greatly effect the weld strength and ultimate tensile strength. Therefore, studying the effect of process parameters is essential in order to optimize FSW process to achieve improved mechanical properties in a weld.

According to a report [Kan10], friction stir welding of aluminum alloy 2219 using a milling machine is carried out successfully. It is reported that tensile strength of welds was significantly affected by welding speed and shoulder diameter whereas welding speed strongly affected percentage elongation and a maximum joining efficiency of 75% was obtained for welds with reasonably good percentage elongation.

R. Karthikeyan and V. Balasubramanian [Kar10], studied FSW parameters such as tool rotational speed, plunge rate, plunge depth, and dwell time play a major role in determining the strength of the joints. An empirical relationship was established to predict the tensile shear fracture load of Friction Stir Spot-Welded (FSSW) AA2024 aluminum alloy by incorporating independently controllable FSSW process parameters. Response surface methodology (RSM) was applied to optimize the FSSW parameters to attain maximum lap shear strength of the spot weld.

Researchers [Jac11] developed a simple three-dimensional thermo-mechanical model for friction stir welding (FSW) that allowed partial sliding between the shoulder and the workpiece. The thermal calculation accounts for conduction and convection effects. The complete thermo-mechanical history of the material during the process can

then be accessed by temperature and strain rate contours. The numerical results are compared with a set of experimental test cases carried out on an instrumented laboratory device.

Mohamadreza Nourani et al., [Moh11], optimized the process parameters of friction stir welding (FSW) of 6061 aluminum alloy, using, ANOVA analysis on the L9 orthogonal array with three factors. Results indicate that among the parameters considered (*i.e.*, the tool rotational speed, transverse speed, and the axial force), the most significant parameter on the weld quality is the rotational speed, followed by the axial force and transverse speed.

According to an experimental work [Cir111], rolled plates of AA 2198 T3 aluminium alloy were used for friction-stir welding varying two fundamental process parameters: rotational and welding speeds. They developed two sets of empirical models based on regression analysis, one for welding force and the other for mechanical strength of the welded joints. Model accuracy is reported to be 95% confidence level. C. N. Suresha et al., [Sur11], attempted to identify the most influencing significant parameter and percentage contribution of each parameter on tensile strength of friction stir welded AA 7075–T6 aluminium joints by conducting minimum number of experiments using Taguchi orthogonal array and developed a model for optimization.

C. Blignault, et al., [Bli12] developed FSW model using different tool pin geometries, and these data were statistically analyzed to determine the relative influence of a number of combinations of important processes and tool geometry parameters on tensile strength. The model reported in their study allowed the weld tensile strength to be predicted for other combinations of tool geometry and process parameters within an average error of 13%. I. Dinaharan and N. Murugan, in their study [Din12] used a variety of ceramic particles that are added to aluminum alloys to produce aluminum matrix composites. They attempted friction stir welding of AA6061/ ZrB2. A mathematical model was developed incorporating the FSW process parameters to predict the ultimate tensile strength. It is reported that the process parameters independently influence the Ultimate Tensile Strength (UTS) over the entire range studied in this work.

3.0 Statement of the problem

In current manufacturing scenario, to ensure the balance between quality and cost of the products, and to increase the machining effectiveness, it is imperative to select the machining parameters. The success of manufacturing largely depends on the selection of process parameters (cutting parameters in case of the machining, forging parameters in case of extrusion, welding parameters in case of friction stir welding). Manual selection ineffective in dynamic manufacturing environments and deterministic approaches are

computationally complex, laborious and often fail to achieve global optimal solutions and converges slowly in large search spaces [Odu05; Deb01]. The increasing complexity of non linear manufacturing processes makes selection of optimal parameters further more difficult and demand simple yet efficient and robust algorithms that can produce quality solutions in reasonable time. Here, nature inspired algorithms can be very useful as they can handle complexity and uncertainty and can improve the effectiveness of machining and fabrication and in turn help in meeting the mutually conflicting objectives of current manufacturing environment, i.e., quality and cost.

Therefore, there is a growing attraction of NIAs for manufacturing optimization [Jam11]. Artificial bee colony (ABC) algorithm and its variants are chosen for the current study. ABC needs to be further improved and can be used for solving real world manufacturing optimization problems. The other popular NIA that exploits principles is quantum inspired evolutionary algorithm (QIEA). The review also suggests that, most of the experiments that have been published are conducted to compare QIEAs with GAs. There are few or no convincing comparisons between QIEAs and ABC based optimization algorithms. So far, the application of QIEAs is focused more on scheduling, graph theoretic, and combinatorial optimization problems. Therefore the potential of QIEAs is further needs to be investigated on manufacturing optimization. Further, there are few studies that reflect the performance analysis ABC algorithm and QIEAs for the aforesaid manufacturing optimization problems. Although, manufacturing process optimization problems of turning, milling, grinding, drilling, etc have been attempted to solve using GA, SA, PSO and DE there is a potential scope to achieve improved quality solutions by exploring other NIAs such as ABC and QIEA. The optimization of friction stir welding using NIAs is largely unexplored area of research.

The frame work of the proposed research is to develop two nature inspired algorithms, one that emulates the intelligent behavior of honeybees, i.e., swarm intelligence based algorithm and the other that exploits the principles of quantum mechanics such as superposition, and observation, i.e., quantum inspired evolutionary algorithm, for the optimization problems of turning, milling, grinding and drilling. Friction stir welding model will be developed using ANN/ANFIS/RSM techniques, which will act as fitness evaluator for the optimization. Experimental studies on FSW will be carried out to generate data for the above model and the results obtained by NIAs will be validated experimentally.

4.0 Objectives of the proposed research

1. To develop new hybrid Artificial Bee Colony (ABC) algorithm for the optimization of intelligent manufacturing systems and analyze its performance on standard test functions.

2. To apply hybrid ABC to intelligent manufacturing optimization problems such as machining and determine its suitability and effectiveness by analyzing its performance on standard performance metrics and comparing it with the other state of the art algorithms.

3. To develop a Quantum Inspired Evolutionary Algorithm (QIEA) for the optimization of intelligent manufacturing systems, and analyze its performance on standard test functions.

4. To apply QIEA to intelligent manufacturing optimization problems such as machining and determine its suitability and effectiveness by analyzing its performance on standard performance metrics and comparing it with the other state of the art algorithms.

5. To compare the performance of hybrid ABC and QIEA on standard numerical optimization problems and manufacturing optimization problems.

6. To model FSW processes for Aluminum alloys using ANN/ANFIS/RSM techniques and optimize the same using NIAs. Experimental validation of results of optimization will also be attempted through tensile test, impact test, hardness test and microstructure evaluation of the weld specimen fabricated with optimal process parameters.

5.0 Methodology

1. Study and development of hybrid artificial bee colony (ABC) algorithm.
2. Coding of the hybrid ABC algorithm in Matlab environment and testing it on standard test functions.
3. Applying the hybrid ABC algorithm on optimization problems of manufacturing such as turning, drilling, milling, grinding and determining the effectiveness of the algorithm for the same.
4. Analyzing the performance of hybrid ABC algorithm, on standard performance metrics (Best, Worst, Mean, Standard deviation, No. of fitness evaluations) for standard test functions and the problems of manufacturing optimization with respect to other evolutionary algorithms reported in literature.
5. Study of quantum inspired evolutionary algorithm (QIEA).
6. Coding QIEA in Matlab environment and testing it on standard test functions.
7. Applying the QIEA on optimization problems of intelligent manufacturing systems such as turning, drilling, milling, grinding and determining the effectiveness of the algorithm for the same. For example, in case of turning the input parameters for the model are cutting speed, feed rate, depth of cut which optimize objective functions such as surface roughness, tool wear etc., in case of grinding model the depth of cut and grit size, feed rate, depth of cut, and grit size are the decision variables that optimize material removal rate, in case of turn-milling model the decision variables are feed rate, depth of cut, cutting speed, speed of the tool which optimize the surface roughness, and in case of drilling model the decision variables are feed rate, cutting speed and objective functions are surface roughness, tool wear etc.
8. Analyzing the performance of QIEA, on standard performance metrics (Best, Worst, Mean, Standard deviation, No. of fitness evaluations) for standard test functions and the problems of manufacturing optimization with respect to other evolutionary algorithms reported in literature.
9. Analyzing the performance of hybrid ABC algorithm and QIEA on optimization problems of intelligent manufacturing systems.
10. Experimentally generating data of FSW process for Aluminum alloys by varying its process parameters such as tool rotational speed (rpm), welding traverse speed (mm/min), plunge depth (mm), geometrical shape of the tool (Conical, Square etc.), and develop ANN/ANFIS/RSM models
11. Optimization FSW models using NIAs
12. Validating the results of NIAs experimentally.

References

[Ale08] Alec Banks, Jonathan Vincent, Chukwudi Anyakoha: "A review of particle swarm optimization. Part II: hybridisation, combinatorial, multicriteria and constrained optimization, and indicative applications". *Nat Comput,* (2008) 7:109–124. DOI 10.1007/s11047-007-9050-z

[Ali09] Ali Rıza Yıldız: "A novel particle swarm optimization approach for product design and manufacturing", *Int J Adv Manuf Technol,* (2009), 40:617–628. DOI 10.1007/s00170-008-1453-1

[Bah10] Bahriye Akay, Dervis Karaboga: "Artificial bee colony algorithm for large-scale problems, and engineering design optimization", *J Intell Manuf*, (2010). DOI 10.1007/s10845-010-0393-4.

[Bli12] Blignault C., Hattingh D.G., James M.N.: "Optimizing Friction Stir Welding via Statistical Design of Tool Geometry and Process Parameters", *JMEPEG*, (2012), 21:927–935. DOI: 10.1007/s11665-011-9984-2

[Bon99] Bonabeau E., Dorigo M., Theraulaz G.: "Swarm Intelligence: From Natural to Artificial Systems", *Oxford University Press*, NY, (1999).

[Box87] Box GEP, Draper NR: "Empirical model-building and response surface". Wiley, New York (1987).

[Car00] Carlyle WM, Montgomery DC, Runger GC: "Optimization problems and method in quality control and improvement". *J Qual Technol*, (2000), 32:1–17.

[Cha10] Chandrasekaran M., Muralidhar M., Murali Krishna C, Dixit U.S.: "Application of soft computing techniques inmachining performance prediction and optimization: a literature review", *Int J Adv. Manuf Technnol*, (2010), 46:445 – 464.

[Cha12] Chauhan S. R., Kali Dass: "Optimization of Machining Parameters in Turning of Titanium (Grade-5) Alloy Using Response Surface Methodology", *Materials and Manufacturing Processes*, (2012), 27(5):531-537.

[Chr05] Christian Blum: "Ant colony optimization: Introduction and recent trends". *Physics of Life Reviews*, (2005), 2:353–373.

[Cir11] Ciro Bitondo , Umberto Prisco, Antonino Squilace, Pasquale Buonadonna, Gennaro Dionoro: "Friction-stir welding of AA 2198 butt joints: mechanical characterization of the process and of the welds through DOE analysis", *Int J Adv Manuf Technol*, (2011), 53:505–516. DOI 10.1007/s00170-010-2879-9

[Deb01] Deb K.: "Multi-Objective Optimization using Evolutionary Algorithms", *Wiley-Interscience Series in Systems and Optimization. John Wiley & Sons, Chichester*, (2001).

[Der12] Dervis Karaboga, Beyza Gorkemli , Celal Ozturk, Nurhan Karaboga: "A comprehensive survey: artificial bee colony (ABC) algorithm and applications", *Artif Intell Rev*, (2012). DOI 10.1007/s10462-012-9328-0

[Der09b] Dervis Karaboga, Bahriye Akay: "A comparative study of Artificial Bee Colony algorithm", *Applied Mathematics and Computation,* (2009), 214:108–132.

[Der09a] Dervis Karaboga, Bahriye Akay: "A survey: algorithms simulating bee swarm intelligence", *Artif Intell Rev,* (2009) 31:61–85. DOI 10.1007/s10462-009-9127-4

[Der07] Dervis Karaboga, Bahriye Basturk: "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm*". J Golb. Optim* (2007), 39:459-471.

[Der05] Dervis Karaboga: "An idea based on honeybee swarm for numerical optimization," *Technical Report TR06,* (2005).

[Din12] Dinaharan I., Murugan N.: "Optimization of Friction Stir Welding Process to Maximize Tensile Strength of AA6061/ZrB2 In-Situ Composite Butt Joints", *Met. Mater. Int.,* (2012), 1(18):135-142. DOI: 10.1007/s12540-012-0016-z

[Dor96] Dorigo M, Maniezzo V, Colorni A: "Ant System:Optimization by a colony of cooperating agents". *IEEE Trans Syst Man Cybernet Part B* (1996), 26(1):29–41.

[Ero11] Erol Kilickap, Mesut Huseyinoglu, Ahmet Yardimeden: "Optimization of drilling

parameters on surface roughness in drilling of AISI 1045 using response surface methodology and genetic algorithm", *Int J Adv Manuf Technol,* (2011), 52:79–88. DOI 10.1007/s00170-010-2710-7

[Esm09] Esmat Rashedi, Hossein Nezamabadi-pour, Saeid Saryazdi: "GSA: A Gravitational Search Algorithm", *Information Sciences,* (2009), 179:2232–2248.

[Fog66] Fogel L. J., Owens A. J., and Walsh M. J.: "Artificial Intelligence Through Simulated Evolution", *Wiley Publishing,* (1966).

[Gex11] Gexiang Zhang: "Quantum-inspired evolutionary algorithms: a survey and empirical study", *J Heuristics* (2011), 17: 303–351. DOI 10.1007/s10732-010-9136-0

[Gro07] Grosan C., Abraham A.: "Hybrid Evolutionary Algorithms: Methodologies, Architectures, and Reviews", *Studies in Computational Intelligence (SCI),* (2007), 75:1-17.

[Hai10] Haiyan Zhao, Zhili Pei1, Jingqing Jiang, Renchu Guan, Chaoyong Wang, and Xiaohu Shi: "A Hybrid Swarm Intelligent Method Based on Genetic Algorithm and Artificial Bee Colony", *ICSI 2010, Part I, LNCS,* (2010), 6145:558–565.

[Han00] Han, K., Kim, J.: "Genetic quantum algorithm and its application to combinatorial optimization problem". *In: Proc. CEC,* (2000), 2:1354–1360.

[Han02] Han, K., Kim, J.: "Quantum-inspired evolutionary algorithm for a class of combinatorial optimization". *IEEE Trans. Evol. Comput*, (2002), 6(6):580–593.

[Han07] Hans Raj K, Rahul S, Rajat S, Swarup A, Rochak J: "A Quantum Seeded Evolutionary Computational Technique for Constrained Optimization in Engineering Design", *Proceedings in the XXXI National Systems Conference,*(2007), 1:876-881.

[Han05] Hans Raj K, Sharma R S, Mishra G S, Dua A, Patvardhan: An evolutionary computational technique for constrained optimisation of engineering design, *Institution of Engineers (India) Journal,* (2005), 86:121-128.

[Han04] Hans Raj K., Sanjay Srivastava, Kamal Srivastava and Rahul Swarup Sharma: "Multi-Objective process optimization of hot closed die forging for intelligent Manufacturing", *International Journal of Agile Manufacturing*, (2004), 4(1):61-70.

[Hin99] Hinterding, R.: "Representation, constraint satisfaction and the knapsack problem". *In: Proc. CEC,* (1999):1286–1292.

[Hol75] Holland J. H.: "Adaptation in Natural and Artificial Systems". *University of Michigan Press (Ann Arbor),* (1975).

[Ivo11] Ivona Brajevic, Milan Tuba, and Milos Subotic: "Performance of the improved artificial bee colony algorithm on standard engineering constrained problems", *International Journal of Mathematics and Computers in Simulation*, (2011), 2(5):135-143.

[Jac11] Jacquin D., Meester B. de, Simar A., Deloison D., Montheillet F., Desrayaud C.: "A simple Eulerian thermomechanical modeling of friction stir welding", *Journal of Materials Processing Technology*, (2011), 211: 57–65.

[Jam11] James M. Whitacre: "Recent trends indicate rapid growth of nature-inspired optimization in academia and industry", *Computing,* (2011), 93:121–133. DOI 10.1007/s00607-011-0154-z

[Jan10] Janakiraman V. and Saravanan R. "Concurrent optimization of machining process parameters and tolerance allocation", *Int J Adv Manuf Technol,* (2010), 51:357–369. DOI 10.1007/s00170-010-2602-x

[Kan11] Kantheti Venkata Murali Krishnam Raju, Gink Ranga Janardhana, Podaralla Nanda Kumar and Vanapalli Durga Prasada Rao: "Optimization of Cutting Conditions for Surface Roughness in CNC End Milling", *International Journal of Precision Engineering and manufacturing*, (2011), 3 (12): 383-391.DOI: 10.1007/s12541-011-0050-7

[Kan10] Kanwer S. Arora, Sunil Pandey, Michael Schaper, Rajneesh Kumar: "Effect of process parameters on friction stir welding of aluminum alloy 2219-T87", *Int J Adv Manuf Technol* (2010), 50:941–952. DOI 10.1007/s00170-010-2560-3

[Kar10] Karthikeyan R., Balasubramanian V.: "Predictions of the optimized friction stir spot welding process parameters for joining AA2024 aluminum alloy using RSM", *Int J Adv Manuf Technol,* (2010), 51:173–183. DOI 10.1007/s00170-010-2618-2

[Kir83] Kirkpatrick S., Gelatt C. D., and Vecchi M. P.: "Optimisation by simulated annealing". *Science*, (1983), 220(4598):671–680.

[Kov12] Kovac P., Rodic D., Pucovsky V., Savkovic B., Gostimirovic M.: "Application of fuzzy logic and regression analysis for modeling surface roughness in face milling", *J Intell Manuf* , (2012). DOI 10.1007/s10845-012-0623-z

[Koj91] Koza J. R.: "Evolving a computer to generate random numbers using the genetic programming paradigm". *In Proceedings of the Fourth International Conference on Genetic Algorithms*, (1991):37–44.

[Kuo11] Kuo-Ming Lee, Ming-Ren Hsu, Jyh-Horng Chou, Ching-Yi Guo: "Improved differential evolution approach for optimization of surface grinding process", *Expert Systems with Applications,* (2011), 38:5680–5686.

[Lak12] Lakshmi V V K, Venkata Subbaiah K: "Modelling and Optimization of Process Parameters during End Milling of Hardened Steel", *International Journal of Engineering Research and Applications (IJERA)* (2012), 2(2):674-679.

[Lea07] Leandro Nunes de Castro: "Fundamentals of natural computing: an overview", *Physics of Life Reviews,* (2007), 4:1–36 (2007). DOI 10.1016/j.plrev.2006.10.002

[Mil10] Milos Subotic: "Artificial bee colony algorithm with multiple onlookers for constrained optimization problems", *Proceedings of the European Computing Conference*, (2010), 251-256.

[Moh11] Mohamadreza Nourani, Abbas S. Milani, Spiro Yannacopoulos: "Taguchi Optimization of Process Parameters in Friction Stir Welding of 6061 Aluminum Alloy: A Review and Case Study," *Engineering*, 2011, 3, 144-155, SciRes. DOI:10.4236/eng.2011.32017

[Nad11] Nadezda Stanarevic, Milan Tuba, Nebojsa Bacanin: "Modified artificial bee colony algorithm for constrained problems optimization". *International journal of mathematical models and methods in applied sciences*, (2011), 3(5): 644-651.

[Nar96] Narayanan, A., Moore, M.: "Quantum-inspired genetic algorithms". *In: Proc. CEC*, (1996):61–66.

[Nur11] Nurhan Karaboga, Mehmet Bahadır Cetinkaya: "A novel and efficient algorithm for adaptive filtering: Artificial bee colony algorithm", *Turk J Elec Eng & Comp Sci*, (2011), 1(19):175-190. doi:10.3906/elk-0912-344

[Odu05] Oduguwa V., Tiwari A., Roy R.: "Evolutionary computing in manufacturing industry: an overview of recent applications", *Applied Soft Computing,* (2005), 5:281–299. DOI:10.1016/j.asoc.2004.08.003

[Okt09] Öktem H.: "An integrated study of surface roughness for modeling and optimization of cutting parameters during end milling operation", *Int J Adv Manuf Technol*, (2009), 43:852–861. DOI 10.1007/s00170-008-1763-3

[Pin11] Pinkey Chauhan1, Kusum Deep, Millie Pant: "Optimizing CNC turning process using real coded gentic algorithm and differential evolution", *Transaction on Evolutionary algorithm and Continuous Optimization,* (2011), 2:157-165.

[Pra11a] Prasanth R.S.S., Hans Raj K.: "Estimation of optimal cutting parameters for minimum surface roughness in tangential turn-milling process using differential evolution algorithm". *Proceedings of national conference Mechanical Engineering Emerging Vistas,* (2011):273-277.

[Pra11b] Prasanth R.S.S., Hans Raj K.: "Application of Differential evolution algorithm for optimizing orthogonal cutting", *Proceedings of International Conference on Systemics, Cybernetics and Informatics, ICSCI,* (2011):122-126.

[Pra11c] Prasanth R.S.S., Hans Raj K.:" Process optimization of plane turning using artificial bee colony algorithm", *Proceedings of National Systems conference, NSC*, (2011):112 – 118.

[Pra12] Prasanth R.S.S., Hans Raj K: "Estimation of optimal cutting parameters of plane turning using quantum inspired evolutionary algorithm", *International Journal of Modern Engineering Research, IJMER,* (2012), 1(2):304-312.

[Rai95] Rainer Storn, Kenneth Price: "Differential Evolution - A simple and efficient adaptive scheme for global optimization over continuous spaces", *TR-95-012* (1995).

[Raj12] Rajmohan T., Palanikumar K.: "Optimization of Machining Parameters for Surface

Roughness and Burr Height in Drilling Hybrid Composites", *Materials and Manufacturing Processes*, (2012), 27(3):320-328.

[Rao09b] Rao R. V., Pawar P J: "Grinding process parameter optimization using non-traditional optimization algorithms", *Proc. IMechE: J. Engineering Manufacture*, (2009), 224(B):887-898. DOI: 10.1243/09544054JEM1782

[Ray09] Raymond Chiong: "Nature-Inspired Algorithms for Optimisation", *Springer*, (2009). DOI 10.1007/978-3-642-00267-0.

[Rec84] Rechenberg I.: "The evolution strategy. a mathematical model of darwinian evolution". In E. Frehland, editor, *Synergetics-from Microscopic to Macroscopic Order*, (1984):122–132.

[Rus95] Russell Eberhart, James Kennedy: "A New Optimizer Using Particle Swarm Theory", *Proceedings of Sixth International Symposium on Micro Machine and Human Science*, (1995): 39-43.

[Sea09] Sean Luke: "Essentials of Metaheuristics", (2009). Available at http://cs.gmu.edu/!sean/book/metaheuristics/

[Sin09] Singh A.: "An artificial bee colony algorithm for the leaf-constrained minimum spanning tree problem". *Appl Soft Comput*, (2009), 9(2):625–631. In: [Der12].

[Sri08] Srikanth T., Kamala V: "A Real Coded Genetic Algorithm for Optimization of Cutting Parameters in Turning", *IJCSNS International Journal of Computer Science and Network Security*,(2008), 8(6):189-193.

[Sur11] Suresha C. N., Rajaprakash B. M. & Sarala Upadhya: "A Study of the Effect of Tool Pin Profiles on Tensile Strength of Welded Joints Produced Using Friction Stir Welding Process", *Materials and Manufacturing Processes*, (2011), 26(9):1111-1116.

[Ton10] Tongchao ,Ding, Song Zhang, Yuanwei, Wang, Xiaoli Zhu: "Empirical models and optimal cutting parameters for cutting forces and surface roughness in hard milling of AISI H13 steel", *Int J Adv Manuf Technol*, (2010), 51:45–55. DOI 10.1007/s00170-010-2598-2

[Ved08] Vedat Savas, Cetin Ozay: "The optimization of the surface roughness in the process of tangential turn- milling using genetic algorithm". *International Journal of Advanced Manufacturing Technology*, (2008), 37:335-340.

[Ven12] Venkata Rao R., Kalyankar V. D.: "Parameter Optimization of Machining Processes Using a New Optimization Algorithm", *Materials and Manufacturing Processes*, (2012), 27(9):978-985.

[Wan05] Wang ZG, Rahman M, Wong YS, Sun J: "Optimization of multi-pass milling using parallel genetic algorithm and parallel genetic simulated annealing". *Int J Mach Tools Manufacture*, (2005), 45:1726–1734.

[Yil09] Yildiz AR: "A novel hybrid immune algorithm for optimization of machining parameters in milling operations". *Rob Comput Integr Manuf*, (2009), 25:261–270.

[Zor10] Zoran Jurkovic, Goran Cukor, Imrich Andrejcak: "Improving the surface roughness at longitudinal turning using the different optimization methods", *Technical Gazette*, (2010), 17(4):397-402.